Retrieval of Environmental and Geophysical Parameters Through Bayesian Fusion of ERS and RADARSAT Data

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Abstract

Two new Bayesian vector speckle filters have been developed for multi-channel SAR images. This filters incorporate first and second order statistical descriptions of the scene and of the speckle in multi-channel SAR images. Since these new filters present the structure of data fusion control systems, speckle filtering should be regarded as the first step of application oriented control systems to exploit the synergy between SAR sensors. Such a control system allowing the retrieval of soil roughness and soil moisture as well as the identification of snow covered areas from ERS and Radarsat images through Bayesian data fusion is presented. Results show that: 1) the new speckle filters present convincing performances for speckle reduction as well as for texture preservation and for small scene objects detection, 2) the retrieval of soil roughness and soil moisture as well as the identification of snow covered areas through Bayesian data fusion of ERS and Radarsat data provide valuable results.

Keywords: environmental monitoring, ERS/RADARSAT synergy, soil moisture, soil roughness, snow cover, control systems

Introduction

Important issues of interest in the field of multi-channel SAR images processing remain still open. Among them, the introduction of A Priori knowledge (or guess) in the processing of multi- SAR's images and multi-date SAR images. In the case of mono-channel SAR images, a Bayesian method, the Maximum A Posteriori (MAP) filtering method has already proved to be particularly suited for the restoration of both the radar reflectivity and the textural properties of natural scenes [1].

In the case of multi-channel detected SAR images, as described in [1,2], the i-th component Ri (channel i) of the radar reflectivity vector *R* is obtained when:

$$\partial \mathrm{Ln}(P(I/R))/\partial R_i + \partial \mathrm{Ln}(P(R))/\partial R_i = 0 \quad \text{for } R_i = \hat{R}_{i\,MAP} \qquad (1)$$

where *I* is the speckled intensity vector available in the actual SAR data. P(*I*/*R*) is the joint probability density function (pdf) of the speckle. P(*R*) is the joint pdf of the radar reflectivity, introduced as statistical A Priori information in the restoration process. The first term of Eq. 1, (Maximum Likelihood) accounts for the effects of the compound imaging system. The second term (Maximum A Priori) represents the prior statistical knowledge of the imaged scene. In the Bayesian inference process, induction is influenced by the prior expectations allowed by the prior knowledge of P(*R*). Also the non-linear system and scene effects are taken into account by the restoration process. Therefore MAP speckle filtering can be considered as a controlled restoration of *R*, where A Priori knowledge controls the inference process, allowing an accurate estimation of the radar backscattering coefficients $\sigma^\circ i$.

At this point, additional Bayesian processes can be designed to retrieve important environmental and geo-physical parameters, in a cascade of control processes.

2. Multi-channel scene model

It is now well established that a Gamma pdf would be the most suitable representation of the first order statistical properties of a natural scene. However, to describe these properties as viewed by diverse SAR sensors (different scene physics) or at different dates (scene evolution), there is no analytic multivariate Gamma pdf available. Therefore, we will use in the following a multivariate Gaussian pdf as analytic multi-channel (*i.e.* coupled) scene statistical model. This statistical model is convenient to preserve the mathematical tractability of the problem. In addition, the Gaussian model is still commonly used to describe the statistical properties of natural scenes.

3. Speckle models and MAP filters

Let first consider the case of very different SAR sensors (very different wavelengths, for instance). In this case, it is justified to consider that the speckle is independent between the N image channels. Under this assumption, P(*I*/*R*) can be modelled as a set of N independent Gamma distributions. Under this assumption, the *Gamma-Gaussian MAP filter for multi-channel detected SAR images* (N channels) comes down to the resolution of a set of N scalar equations [2]:

$$\begin{aligned} & L_i(I_i/R_i^2 - 1/R_i) - {}^t(1_i).C_R^{-1}.(R-\langle R\rangle) \\ & - {}^t(R-\langle R\rangle).C_R^{-1}.(1_i) - 1/2\ \mathrm{Tr}[C_R^{-1}.\partial C_R/\partial R_i] \\ & + {}^t(R-\langle R\rangle).C_R^{-1}.\partial C_R/\partial R_i.C_R^{-1}.(R-\langle R\rangle) = 0 \qquad (2) \end{aligned}$$

where Cr is the covariance matrix of the scene, (1i) is a vector where all components but the ith are equal to zero, and the Li are the Equivalent Numbers of Looks (ENL) of the individual SAR images.

Replacing the speckle noise model by the convenient optical noise model in the concerned image channels, this filter adapts easily to the case of multi-channel optical and SAR images. Thus, the introduction of coupling between the scene statistical representations is already a data fusion process.

On the other hand, in the case of multi-date images acquired on repeat-pass by the same SAR sensor, or of a set of images acquired by diverse SAR's with similar properties (similar orbit, track, frequency and resolution, with only different polarisation configuration, or small differences in incidence angle, for example), the correlation of the speckle between SAR image channels should be taken into account to deal optimally with system effects in the series. In theory, P(*I*/*R*) should be a multivariate Gamma pdf. Nevertheless, since there is no analytic multivariate Gamma pdf available, another reasonable choice for P(*I*/*R*) must be done for the sake of mathematical tractability: Lee [3] has shown that, in the case of multilook SAR images (more than 3-looks), P(*I*/*R*) can be reasonably approximated by a Gaussian distribution. Under this assumption, the *Gaussian-Gaussian MAP filter for multi-channel detected multilook SAR images* is the set of equations [2]:

$$\begin{aligned} & {}^t(1_i).C_S^{-1}.(I-R) + {}^t(I-R).C_S^{-1}.(1_i) - 1/2\, \mathrm{Tr}[C_R^{-1}.\partial C_R/\partial R_i] \\ & + {}^t(R-\langle R\rangle).C_R^{-1}.\partial C_R/\partial R_i.C_R^{-1}.(R-\langle R\rangle) \\ & - {}^t(1_i).C_R^{-1}.(R-\langle R\rangle) - {}^t(R-\langle R\rangle).C_R^{-1}.(1_i) = 0 \qquad (3) \end{aligned}$$

where Cs is the covariance matrix of the speckle.

4. MAP filters and control systems

These filters offer numerous advantages, which are described in [2]: non linear image restoration, preservation of high-resolution through the correction of the effects of the compound multi-sensor imaging system, improvement of the probability of detection of thin scene structures due to both the diversity and redundancy aspects of information in all the channels.
Nevertheless, the most remarkable feature is that they present the structure of control systems. Both Eqs. (2) and (3) can be rewritten as Riccati's algebraic equations:

$$- A\,X - X\,{}^tA - Q + X\,{}^tC\,P^{-1}\,C\,X = 0 \qquad (4)$$

Equation (4) represents the optimal state controlled reconstruction at constant gain of linear invariant processes (*R* and textures of the channels) perturbed by white noises (speckle, pixel spatial mismatch between channels). It can easily be shown that the scene A Priori model acts as a command, and that the covariance matrices act as multipoles or controls.

5. Filtering of ERS / RADARSAT data set

This new filtering technique is evaluated on a couple of Radarsat (C-HH) and ERS-1 (C-VV) SAR images, acquired along descending passes within 4 hours on Feb. 13, 1996. Figure 1 (left column) shows a detail of the Radarsat (up) and ERS-1 (bottom) images, around the Schipol-Amsterdam airport in the Netherlands.

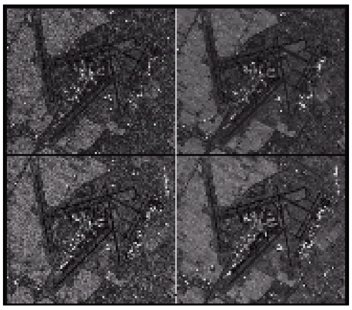

Figure 1: Upper images: original ERS-1 PRI image (13 Feb. 1996, @ESA/Eurimage 1996) and its filtered version. Bottom images: original Radarsat Standard Beam image (13 Feb. 1996, @Radarsat International 1996) and its filtered version (Gaussian-Gaussian MAP filter for multi-channel detected SAR images, 9x9 basic window size).

The Radarsat and ERS SAR's operate at the same frequency from a very similar orbit (similar altitude and inclination angle). In this case, the angles of incidence are also very similar and image superimposition is possible without geometrical corrections over wide areas. The two sensors differ only in polarisation configuration, so that they are sensitive to similar physical properties of extended land areas, even if these properties do not contribute in the same amount to the backscattered signal. However, their different sensitivity to structural scene elements is of major interest for the identification of these particular targets. In this context, it is appropriate to use the new Gaussian-Gaussian MAP filter. The filtered images are shown in Figure 1 (right images). Thin details such as roads, runways, airport terminals, planes, point targets in the built-up areas, are very well denoised and preserved, as it is also the case for field edges. On the other hand, speckle noise is strongly filtered within the surrounding homogeneous agricultural fields (ENL=120 for Radarsat, ENL=100 for ERS-1). For both images, the filtered images were found superior in quality to the images filtered using the mono-channel Gamma-Gamma MAP filter [1] using the same structure detection algorithm [4].

6. Bayesian retrieval of soil parameters

Haddad & Dubois [5] have developed a Bayesian estimation method of soil roughness and soil moisture. Although their method present some built-in limitations (the imaginary part of the dielectric constant ε is not taken into account, no dependence on the surface correlation, *cf.* [6]), it is based on the same principle as our new filtering method and present common theoretical advantages.

Since our data are accurately filtered and calibrated, instead of the model presented in [5], we can use directly the soil backscattering empirical model of Dubois *et al.* [7]:

$$\begin{aligned} \sigma^\circ_{HH} &= m = M_1(\theta,\lambda)\ .\ f(\varepsilon,h) \qquad (5) \\ \sigma^\circ_{VV} &= n = M_2(\theta,\lambda)\ .\ g(\varepsilon,h) \end{aligned}$$

where θ is the wave incidence angle, λ is the radar wavelength, ε is the soil dielectric constant, and h is the r.m.s. height (soil roughness). Using Bayes' theorem, the unnormalised version of the conditional joint probability of (ε ,h) verifies [5]:

$$P(\varepsilon,h|m,n) = P(\varepsilon,h)\ /\ [\ f(\varepsilon,h).g(\varepsilon,h)\ ]\ .\ P(M_1,M_2) \qquad (6)$$

The optimum unbiased estimator for $X \in \{\varepsilon, h\}$ that has minimum variance is the conditional mean [5]:

$$\hat{X} = \int X \,.\, P(\varepsilon,h|m,n)\, d\varepsilon .\, dh \qquad (7)$$

Finally, the dielectric constant is converted to volumetric soil moisture through a set of empirical curves [8].
With our data accurately filtered and calibrated, the nature of the randomness present in (m,n) can only be due to relief. Since our Netherlands area present negligible relief, P(M1,M2) is reasonably assumed a Dirac distribution. This results in a straightforward estimation of P(ε ,h|m,n), *i.e.* a drastic simplification of the process and potentially more accurate results.

Results of this method, applied over the Netherlands (area size 73x63 km), are shown in Figure 2. Note that at this period of the year (February), the low or non-existent vegetation layer does not affect significantly the retrieval of soil parameters over agricultural areas (crops/pasture).

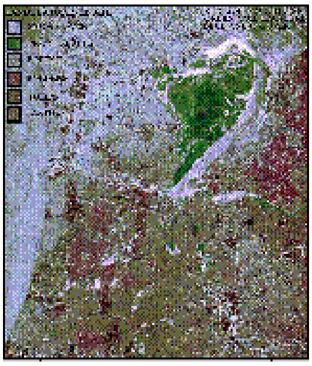

Figure 2: The Netherlands on February 13, 1996. Area size: 73x63 km. Red: soil roughness map. Green: soil moisture map. Blue: snow cover map.
Maps produced using ERS-1 and Radarsat SAR imagery.

As shown in this figure, snow covered areas (thin snow layer of a few centimeters), difficult to identify in the original SAR images, can be identified by simple classification of the soil moisture and roughness maps.
The interest of the quantitative results (especially soil moisture) for the initialisation of agro-meteorological and growth models has already been widely expressed. In addition, since soil roughness (in red) allows also the identification of cultivated areas, such a result can be a useful as a photo-interpretation tool, to support other agriculture applications such as crop surfaces estimation [9], or to monitor special environmental conditions (snow cover, frozen lakes, etc.).

Conclusions

Two new Bayesian speckle filters have been developed for multi-channel SAR images, with very convincing results. The Gaussian-Gaussian MAP filter SAR images is suitable to process series of images from the same SAR system operating in repeat-pass mode or from diverse SAR's systems with relatively close properties. The Gamma-Gaussian MAP filter is suitable to process series of images originating from different SAR systems (different frequencies, incidence angles, or spatial resolution, but same spatial sampling). Combined with the two-points statistics based algorithm presented in [4], these filtering techniques are able to produce filtered images without loss in spatial resolution. Within homogeneous areas, speckle noise is strongly filtered, allowing the accurate estimation of σ° required by most of the remote sensing SAR applications such as the retrieval of soil parameters (roughness and moisture).
The major interest of this technique is that we apply pure control systems. This offers wide possibilities for the choice and the design of additional commands (statistical or physical models) for further data exploitation. In this view, speckle filtering should be regarded as the first step of integrated application oriented control systems rather than of processing chains.

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